PaddyCare AI: A CNN-Based Disease Detection and Nutrient Decision Support System

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Abstract—**Agricultural productivity in paddy cultivation is significantly affected by plant diseases and improper soil nutrient management. Traditional detection and fertilizer application methods are manual, inaccurate, and time-consuming. This project presents PaddyCare AI, a comprehensive intelligent system integrating Convolutional Neural Networks (CNN), Internet of Things (IoT) sensors, and a Qt/QML-based desktop reporting platform. The system performs real-time paddy leaf disease detection using an ESP32-CAM module and monitors soil nutrient levels using an NPK sensor. A lightweight CNN model classifies diseases such as Brown Spot, Leaf Blast, and Hispa with embedded edge inference capability. A rule-based Decision Support System (DSS) recommends appropriate fertilizer and treatment solutions. Furthermore, a Qt-based application generates structured PDF reports. Experimental results demonstrate classification accuracy of approximately 82%. The proposed system offers a low-cost, scalable, and sustainable solution for smart agriculture.**

Keywords— CNN, Decision Support System, ESP32-CAM, IoT, NPK Sensor, Paddy Disease Detection, Precision Agriculture, Qt/QML.

I. INTRODUCTION

Paddy is one of the most widely cultivated cereal crops and serves as a primary food source for a significant portion of the global population. In countries like India, paddy cultivation plays a crucial role in ensuring food security, supporting rural livelihoods, and contributing to the agricultural economy. However, increasing population demand, climate variability, and limited arable land require the adoption of intelligent and sustainable farming practices to enhance productivity. Paddy crops are highly vulnerable to various biotic stresses, particularly fungal diseases and insect infestations. Among the most common and destructive diseases are Brown Spot, Leaf Blast, and Hispa insect damage. Brown Spot, caused by fungal pathogens, leads to circular lesions on leaves that reduce photosynthetic efficiency. Leaf Blast is a severe fungal infection that can spread rapidly under humid conditions, resulting in significant yield loss. Hispa insect infestation damages leaf tissues by scraping chlorophyll-containing cells, thereby affecting plant growth and overall crop health. Early detection and timely treatment of these diseases are essential to minimize economic losses. Apart from disease-related challenges, soil nutrient im-balance is a major factor affecting paddy productivity. The three primary macronutrients required for optimal growth are Nitrogen (N), Phosphorus (P), and Potassium (K). Deficiency or excess of these nutrients results in poor plant development, reduced resistance to stress, and lower yield quality. Conventional soil testing methods are laboratory-dependent and time consuming, making frequent monitoring impractical for many farmers. Traditional disease identification and fertilizer management rely largely on manual inspection and farmer expertise. These approaches are subjective, prone to error, and inefficient for large-scale agricultural fields. Misdiagnosis of plant diseases and incorrect fertilizer application not only reduce crop yield but also increase operational costs and environmental impact. Recent advancements in Artificial Intelligence (AI), Convolutional Neural Networks (CNN), Internet of Things (IoT), and embedded systems have enabled the development of precision agriculture solutions. CNN-based image classification techniques provide accurate plant disease detection, while IoT-enabled soil sensors allow real-time monitoring of nutrient levels. Edge computing platforms such as ESP32 facilitate on- device inference, reducing latency and eliminating continuous cloud dependency. Motivated by these technological advancements, this work proposes PaddyCare AI, an integrated intelligent system that combines CNN-based paddy disease detection, soil nutrient monitoring using NPK sensors, and a rule-based Decision Support System (DSS) for fertilizer and treatment recommendations. The system further incorporates a Qt/QML-based desktop application for structured PDF report generation, enhancing traceability and digital agricultural management. The proposed solution aims to provide a low-cost, scalable, and efficient smart agriculture framework suitable for real- world deployment.

II. RELATED WORK

The application of Artificial Intelligence (AI) and Deep Learning techniques in agriculture has gained significant attention in recent years. Convolutional Neural Networks (CNNs) have emerged as a dominant approach for plant disease detection due to their ability to learn discriminative spatial features directly from images. Several studies have employed deep architectures such as VGG, ResNet, and DenseNet to achieve high classification accuracy in controlled datasets. Transfer learning strategies using pre-trained models have further improved performance, particularly when agricultural datasets are limited in size. Despite promising results, most existing disease detection systems are designed for cloud-based or high-performance computing environments. These implementations introduce communication latency and require continuous internet connectivity, which may not be feasible in rural agricultural regions. Moreover, complex deep learning models demand substantial memory and computational resources, limiting their practical deployment on low-power embedded devices. Parallel advancements in Internet of Things (IoT)-based smart farming systems have enabled real-time monitoring of soil and environmental parameters. NPK sensing technologies, along with soil moisture and temperature monitoring, have been integrated with microcontroller platforms for precision agriculture applications. Although such systems enhance nutrient management and irrigation scheduling, they are typically implemented as standalone monitoring frameworks without integration of intelligent disease diagnosis modules. Recent efforts have attempted to combine AI and IoT technologies for comprehensive farm management. However, most solutions focus either on disease classification or soil analysis independently, lacking a unified architecture that integrates both functionalities within a single embedded platform. Furthermore, structured digital documentation and automated report generation remain underexplored in existing agricultural AI systems. Therefore, a research gap exists in developing a cost- effective, edge-deployable, and integrated intelligent frame- work capable of performing real-time paddy disease detection, soil nutrient analysis, decision support, and systematic digital reporting within a cohesive architecture.

III. OVERALL SYSTEM ARCHITECTURE

PaddyCare AI follows a multi-layered modular architecture designed for real-time embedded intelligence and scalable agricultural deployment. The system integrates sensing, edge computing, artificial intelligence, decision support, and reporting modules.

A. *Sensing Layer*

This layer is responsible for real-time data acquisition from the agricultural field:

- OV2640 camera integrated with ESP32-CAM for high-resolution leaf image capture
- RS485-based Soil NPK sensor for Nitrogen (N), Phosphorus (P), and Potassium (K) measurement

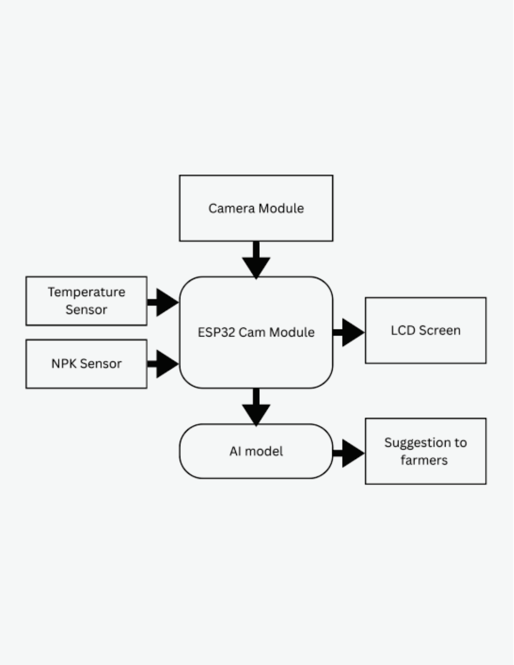

Fig. 1. Block Diagram of PaddyCare AI using ESP32-CAM, sensors, and CNN model

- DHT11/DHT22 temperature and humidity sensor for environmental monitoring

The sensors periodically collect data and transmit it to the processing layer.

B. *Edge Processing Layer*

The ESP32-CAM microcontroller performs:

- Image resizing and normalization
- Noise reduction using Gaussian filtering
- Conversion to RGB tensor format
- Serial communication with NPK sensor

Edge inference reduces latency and eliminates cloud dependency.

C. *AI Classification Layer*

A lightweight Convolutional Neural Network (CNN) model is deployed using TensorFlow Lite for Microcontrollers.

Architecture:

- 3 Convolution layers
- 2 MaxPooling layers
- 1 Fully connected layer
- Softmax output layer (4 classes)

Optimization:

- 8-bit integer quantization for memory and computational efficiency

D. *Decision Support Layer*

This layer combines:

- Rule-based fertilizer recommendation system

- K-means clustering for nutrient categorization
- Disease-treatment mapping database

Based on classified disease and nutrient deficiency, appropriate fertilizer dosage and pesticide suggestions are generated.

E. Application Reporting Layer

A Qt/QML desktop application performs:

- Real-time data visualization
- Disease probability display
- Nutrient status representation
- Automated PDF report generation
- Data logging and historical storage

This ensures structured documentation for farmers and agricultural officers. PaddyCare AI bridges this gap.

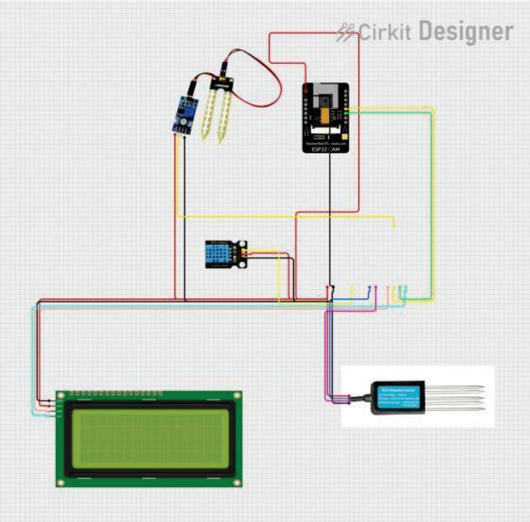

Fig. 2. Circuit Diagram of the proposed system

IV. MATHEMATICAL MODEL OF CNN

A. Convolution Operation

$$Y_{i,j} = \sum_{m}\sum_{n} X_{i+m,j+n} \cdot W_{m,n} + b \qquad (1)$$

Where:

- X = Input feature map
- W = Kernel (filter)
- b = Bias term
- $Y_{i,j}$ = Output feature value

B. Loss Function

$$L = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \qquad (2)$$

Where:

- y_i = True label
- $\hat{y}_i$ = Predicted probability
- C = Number of classes

Optimizer: Adam
Learning Rate: 0.001

V. DATASET AND TRAINING SETUP

A. Dataset Description

The dataset used in this study consists of paddy leaf images collected from publicly available agricultural image repositories and field-level captures using the ESP32-CAM module.

The dataset contains four classes:

- Healthy
- Brown Spot
- Leaf Blast
- Hispa

B. Dataset Split and Preprocessing

The dataset was divided as follows:

- Training set: 80% (960 images)
- Validation set: 10% (120 images)
- Test set: 10% (120 images)

All images were resized to a fixed resolution of 128×128 pixels to maintain uniform input dimensions for the CNN model. Data preprocessing steps included normalization (pixel scaling between 0 and 1) and noise reduction.

Data augmentation techniques such as rotation, horizontal flipping, zooming, and brightness adjustment were applied to improve model robustness against real-field variations such as lighting conditions and leaf orientation.

C. Training Configuration

The CNN model was trained using the TensorFlow framework and later converted to TensorFlow Lite format for embedded deployment. The training configuration parameters are as follows:

- Batch size: 32
- Number of epochs: 40
- Learning rate: 0.001
- Optimizer: Adam
- Activation function (hidden layers): ReLU
- Output layer activation: Softmax
- Loss function: Categorical Cross-Entropy

The Adam optimizer was selected due to its adaptive learning capability and faster convergence compared to traditional stochastic gradient descent (SGD). ReLU activation was used in hidden layers to introduce non-linearity and reduce vanishing gradient issues, while the Softmax function was applied in the output layer to generate class probability distributions. Early stopping and validation monitoring were implemented to prevent overfitting. The model achieving the highest validation accuracy was selected for final testing and deployment.

D. Model Deployment Preparation

After training, the model was quantized to 8-bit integer precision to reduce memory footprint and computational complexity. The optimized model was then deployed on the ESP32-CAM module for real-time edge inference. This approach ensures low latency and eliminates dependency on

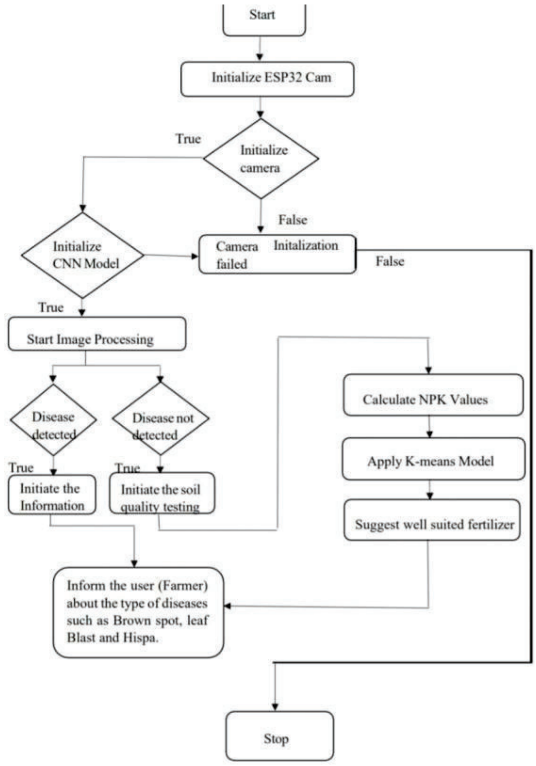

Fig. 3. System workflow for paddy disease detection and fertilizer recom-mendation

cloud-based computation. A total of approximately 1200 labeled images were used for training and evaluation.

VI. PERFORMANCE EVALUATION

TABLE I
PERFORMANCE METRICS

Metric	Value
Accuracy	82%
Precision	80%
Recall	81%
F1-Score	80.5%

VII. QT/QML REPORT GENERATION MODULE

The Qt/QML-based application is responsible for user interaction, visualization, and report generation. It performs the following functions:

- Serial communication with ESP32
- Display of disease classification results
- Display of NPK sensor values
- Generation of structured PDF reports

A. PDF Generation Flow

The PDF report generation process follows these steps:

1) Data retrieval from the ESP32 and sensors
2) Template formatting using predefined report layouts
3) Export to PDF using QPrinter
4) File storage with timestamp for record keeping

PaddyCare
Rice Disease Monitoring — Field Report
Generated: 13 April 2026 16:39:48

Current Readings

Parameter	Value	Unit
Temperature	35.20	°C
Humidity	23.60	%
Soil Moisture	77	%
Nitrogen (N)	61	mg/kg
Phosphorus (P)	59	mg/kg
Potassium (K)	62	mg/kg
Disease	Hispa	
Confidence	0.57	
Fertilizer	NPK19-19-19	

NPK Distribution

Fertilizer Reference Guide

Deficiency	Recommended	Full Name
Nitrogen (N)	Urea / DAP	Di-Ammonium Phosphate
Phosphorus (P)	SSP	Single Super Phosphate
Potassium (K)	MOP	Muriate of Potassium
Current pick	NPK19-19-19	NPK 19-19-19 Compound

Fig. 4. An example of report.

This module enhances traceability, documentation, and supports efficient digital agriculture management.

VIII. FUTURE SCOPE

The proposed PaddyCare AI system provides a strong foundation for intelligent precision agriculture. However, several enhancements can be implemented in future research to improve scalability, intelligence, and real-world adaptability.

- **Mobile Application Integration:** Development of an Android/iOS application for real-time disease detection, nutrient monitoring, and farmer-friendly visualization with multilingual support.
- **Cloud-Based Analytics Platform:** Integration with cloud infrastructure to enable large-scale farm monitoring, historical data analysis, predictive modeling, and remote expert consultation.
- **Transformer-Based Vision Models:** Upgrading the CNN architecture to lightweight Vision Transformer (ViT) or hybrid CNN-Transformer models for improved feature extraction and classification accuracy.
- **Multi-Crop Disease Detection:** Extending the framework to support additional crops such as wheat, maize, and pulses by retraining and expanding the dataset.
- **Automated Irrigation Integration:** Integration with smart irrigation systems to provide automated water management based on soil nutrient and environmental parameters.

These improvements will transform the proposed system into a fully autonomous, scalable, and intelligent smart farming ecosystem capable of supporting sustainable agricultural practices.

IX. LIMITATIONS

- **Moderate Dataset Size:** The dataset contains approximately 1200 images, which may limit model generalization across diverse geographical regions and varying crop conditions.
- **Limited Disease Classes:** The current model is trained on only four classes (Healthy, Brown Spot, Leaf Blast, and Hispa). Additional diseases are not covered in this version.
- **Sensor Calibration Requirement:** NPK sensor readings may drift over time due to soil moisture variations and environmental factors, requiring periodic calibration for accurate measurement.

X. RESULTS AND PERFORMANCE EVALUATION

The proposed PaddyCare AI system was tested under real-time conditions using an integrated hardware and software setup consisting of the ESP32-CAM module, NPK soil sensor, and Qt-based desktop application.

A. Experimental Output

The proposed system successfully performed end-to-end processing,including image acquisition, disease classification, nutrient sensing, and recommendation generation.

- **Disease Detection:** The CNN model correctly identified paddy leaf diseases such as *Hispa* and *Leaf Blast* from captured images.
- **NPK Sensor Output:** Real-time soil nutrient values were obtained from the RS485-based sensor:
  - Nitrogen (N): ~60mg/kg
  - Phosphorus (P): ~62mg/kg
  - Potassium (K): ~61mg/kg
- **Fertilizer Recommendation:** Based on detected nutrient deficiency, the system recommended appropriate fertilizer actions such as MOP(Mutriate of potash).
- **LCD Display Output:** The embedded LCD module displayed:
  - Detected disease (e.g., Leaf Blast)
  - Fertilizer suggestion (e.g., Add Nitrogen)
  - Real-time NPK values
- **Desktop Application Output:** The Qt/QML-based interface displayed:
  - Disease classification (e.g., Hispa)
  - Nutrient status visualization
  - Fertilizer recommendations

B. System Performance

The model achieved an approximate classification accuracy of 82% on the test dataset. The deployment of the quantized TensorFlow Lite model on ESP32 ensured low-latency inference suitable for real-time applications.

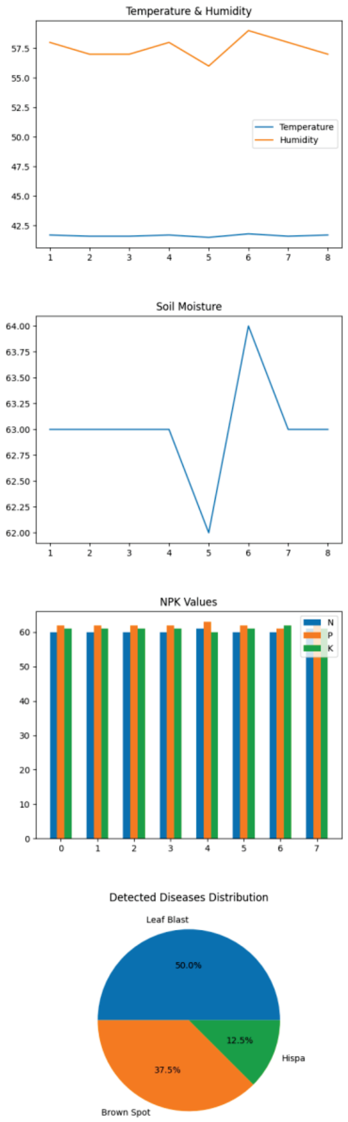

Fig. 5. Comparative analysis of system inputs and diagnostic outputs, including NPK nutrient levels, soil classification, and detected plant diseases.

C. Observations

The experimental results demonstrate that the system is capable of:

- Real-time disease detection using edge AI
- Accurate soil nutrient monitoring
- Automated decision support for fertilizer application
- Seamless integration of hardware and software components

Overall, the system validates the feasibility of deploying AI-driven precision agriculture solutions using low-cost embedded platforms.

Fig. 6. Detected disease classification result using trained model

XI. CONCLUSION

PaddyCare AI represents an integrated intelligent precision agriculture system designed for real-time paddy disease detection and soil nutrient analysis. The proposed framework com-bines a lightweight CNN-based image classification model, IoT-enabled NPK sensing, and a rule-based Decision Support System (DSS) within a unified embedded architecture. Deployment on the ESP32-CAM platform using a quantized TensorFlow Lite model enables efficient edge-based inference with-out cloud dependency. Experimental evaluation demonstrated a classification accuracy of approximately 82%, validating the effectiveness of the approach under controlled and semi-field conditions. The integration of soil nutrient monitoring enhances agricultural decision-making by generating fertilizer recommendations based on real-time NPK measurements. In addition, the Qt/QML-based desktop application provides structured visualization and automated PDF report generation, improving documentation, traceability, and digital farm management. The integration of AI, IoT, embedded systems, and intelligent reporting mechanisms establishes a cost-effective, scalable, and sustainable framework for smart paddy cultivation. The system contributes to precision agriculture by reducing manual intervention, minimizing crop losses, optimizing fertilizer usage, and supporting environmentally responsible farming practices.

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